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Analysis of Student Learning Behavior using Process Mining and Spectrogram

Anake Nammakhunt* and Wichian Premchaiswadi
Graduate School Information Technology, Siam University, Bangkok 10160, Thailand
*E-mail: anake.nam@siam.edu

Abstract

This study aims to present an analysis using Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis to examine factors affecting the efficiency of teaching management and the relationship between the frequency of attendance and the duration of attendance on academic achievement. The tools employed in this study include event log data analyzed using Process Mining techniques with the Fuzzy Miner algorithm and Spectrogram Analysis through the Matplotlib Library of Python. The sample group consisted of 247 undergraduate students from a private university in Thailand, selected using a purposive sampling method. The results of the Spectrogram Analysis reveal a clear distinction in the continuity of the learning process between groups with academic achievement above 70% and below 70%. The frequency of attendance is positively correlated with the duration of attendance at a statistical significance level of 0.01, and the frequency of attendance (Beta = 0.537) is a significant factor affecting the efficiency of teaching management at a statistical significance level of 0.01. Therefore, it is possible to integrate techniques of Process Mining, Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis to discover and confirm methods for developing teaching processes, improving teaching quality, enhancing students' learning experiences, and driving e-learning systems to achieve better academic outcomes, promoting continuous awareness and learning.

Keywords: Process Mining, Process Discovery, Learning Behavior, Spectrogram, Education Process Mining.

1. Introduction

Many educational institutions in Thailand have utilized e-learning as a significant mechanism for online education management, enabling continuous self-directed learning (1). This learning process emphasizes putting students at the center (2), fostering avenues for reviewing lessons and stimulating learning. Learning in this format necessitates utilizing technology or online mediums, which help reduce constraints regarding time and location. Instructors can present various learning approaches, and learners can choose topics of interest, distinguishing them from traditional classroom learning, where students must adhere to fixed schedules and may encounter environmental disruptions, leading to incomplete learning experiences. E-learning helps mitigate these drawbacks, allowing learners to plan their studies independently, such as scheduling their study times, creating visual media experiences like images, videos, and graphics to enhance understanding, and opting for review or skipping content.

Conversely, online learning outcomes may vary if learners are assigned to study independently without specific objectives (3). However, there is still a limited understanding of online learning processes and student behaviors from e-learning system event log data (4). Understanding actual student behavior processes would enable instructors to set conditions to create incentives for student learning (5).

Given the importance as mentioned above, we are interested in studying the spectrogram analysis of students' learning behaviors using event log data from process mining techniques in e-learning systems, which are significant for understanding students' learning behaviors. Analysis of spectrograms from the research literature has found that most spectrogram analyses are used to assess the condition of machinery, aiding in the detection and identification of failure modes in rotating shafts to detect flaws in the bearings or components used to reduce friction between rotating parts and other parts in machinery or equipment. Spectrogram analysis has been used to detect internal engine faults (6), radiation exposure (7), and sound wave systems (8). In this article, a case study analyzes the spectrogram behavior of students learning through e-learning systems using event log data processed through process mining techniques (4, 9, 10) and educational process mining (11–13) as a guide for developing e-learning teaching processes, improving teaching quality, enhancing student learning experiences, resulting in improved learning outcomes, and enabling students to adapt to e-Learning more quickly, become familiar with self-directed learning, and continue learning throughout their lives (14).

This study's key contribution lies in its innovative approach to analyzing e-learning systems. We propose an approach that leverages event log data processed through process mining techniques. This data is further analyzed using Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis. This comprehensive, data-driven approach generates valuable insights to guide the teaching and learning management process within the e-learning system. Additionally, to explore student learning behavior in more depth, we apply event log data processed through process mining techniques to compare two groups: high-achieving students (above 70% academic achievement) and students with lower achievement (below 70%). This comparative analysis aims to identify potential differences in their learning patterns.

2. Theory and related research

Electronic learning (e-learning) is an educational management system or learning method that requires learners to have self-directed learning skills to promote readiness for learning (15). Learners can acquire knowledge from prepared sources and resources through electronic media, which are presented interestingly. E-learning relies on various technology branches that adapt to technological changes and eras. Meanwhile, the convenience and abilities of instructors toward learners affect their satisfaction level (16, 17).

A Learning Management System (LMS) is a network-based or online learning management system allowing learners to study independently anytime, anywhere. It provides learning tools, including course management, content and activity creation, lesson organization, activity and exercise management, test management, learner management, communication and interaction tool management, and learning process organization. It handles access, data storage, reporting, and management systems for administrators. Moodle is an example of an LMS and is a tool for managing online teaching and learning through the Internet (18, 19).

Process mining is a data analysis technique that focuses on the behavior within event log data (20), divided into three parts: 1) Process Discovery, 2) Conformance Checking, and 3) Enhancement, displaying the results as a Process Map (21) of activities derived from event log data. It serves as a tool to discover how work processes occur by comparing them with existing models or theoretical processes (22), aiming to study feasible processes for developing operational processes to achieve goals.

Event log processing involves analyzing data collected from an organization's information systems. This data, known as event logs, is typically stored in structured formats such as relational databases or semi-structured formats like text files (e.g., Text, CSV) or XML. Each event log entry contains metadata about an event that occurred, including the user who performed the action (user ID), the timestamp of the event, the specific activity performed, and potentially the location where the action took place. The design of event logs should consider the data requirements of process mining analysis and understand the needs of each algorithm before designing event logs to ensure events meet the requirements before analysis. This is crucial for effective analysis. Event logs are real datasets from systems consisting of four main parts: 1) Case, 2) Activity, 3) Resource, and 4) Timestamp (20, 23).

Education Process Mining (EPM) is the understanding and predicting student learning behavior. Algorithms such as the Inductive Visual Miner (IvM) and Directly Follows Visual Miner (DFvM) can be used to assess the efficiency and evaluate student learning patterns and behaviors in teaching and online learning processes. Personalized learning and parental involvement in improving student learning outcomes can also be analyzed. Process mining techniques can provide valuable insights for enhancing teaching quality and enriching students' learning experience (11–13).

3. Research process

This research employed a targeted sampling approach, selecting 247 students enrolled in the 202111 Applied Business Programming course. The research process comprised five steps: 1) Event Log Data Generation: Creating CSV format event log data from the Learning Management System (LMS) involved data collection and analysis using process mining techniques to identify student learning behavior patterns. 2) Sample Grouping: Dividing the sample into two groups: Group 1 comprising students scoring 70% or above, and Group 2 consisting of students scoring below 70%. This step was a data filtering process to obtain genuine event log data for both groups before exporting event logs in CSV format. 3) Spectrogram Analysis: Utilizing the CSV data from step 2 to study the attendance behavior of both groups, determining if there are differences in attendance frequency and its impact on exam results. 4) Correlation Analysis: Examining the relationship between attendance frequency, attendance duration, and obtained scores to ascertain if there is a correlation. 5) Multiple Linear Regression Analysis: Analyzing multiple factors influencing teaching management effectiveness. The aim was to demonstrate the application of Process Mining in e-learning teaching management, showcasing deep-seated student behaviors aligned with Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis. These five steps collectively constitute a research process that enables the research to achieve objectives related to the application of Process Mining alongside Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis.

3.1 Create event log data from the learning management system (LMS) in CSV file format.

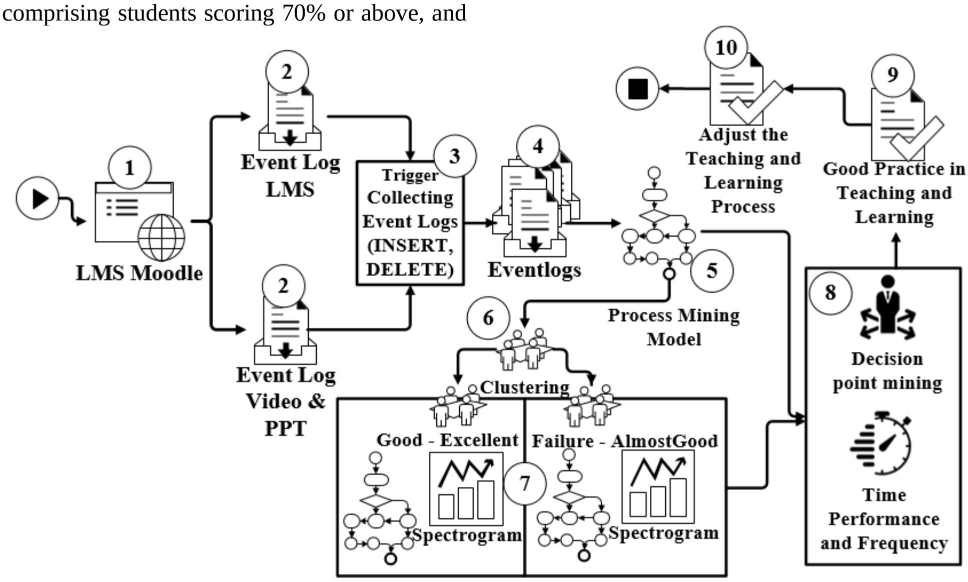


Figure 1 Illustrates the process of generating event log data for exporting in CSV file format.

Figure 1 illustrates the process of creating event logs, starting from Step 1, the Learning Management System (LMS), to Step 2, collecting student event logs, such as accessing instructional media, answering questions, taking tests, and other activities. In Step 3, trigger-based data processing is employed to automatically generate and collect e-learning event logs whenever INSERT or UPDATE events occur within the LMS database (4). Step 4 subsequently exports the data in CSV file format, as depicted in Figure 2, consisting of:

1. The 'idnumber' column stores the unique student ID for identifying each student's learning activities through the system. We designate this as the Case ID for each sub-activity arising from individual students' behavior.

2. The 'Datecreate' column stores the date and time of students' learning activities.

3. The 'eventname' column stores data on students' learning behavior in each activity.

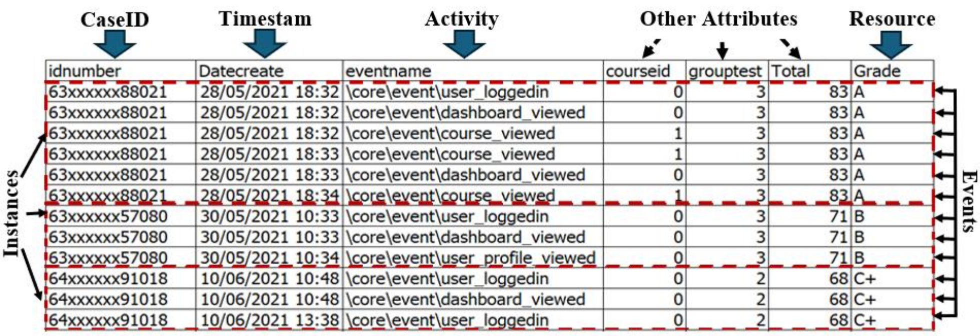
4. The 'courseid' column stores the course code for the courses students are enrolled in.

5. The 'grouptest' column stores information on student groups, including Morning Shift 4 Years, Morning Shift 2 Years, and Sunday Shift.

6. The 'Total' column stores the total cumulative scores.

7. The 'Grade' column stores students' academic performance data.

In Step 5, the event log data extracted in Step 4 is analyzed for process discovery using process mining techniques. The Disco tool, employing the Fuzzy Miner algorithm, is utilized for this purpose. This analysis revealed that during the e-learning sessions of the sample group of 247 students, there were 461,511 events encompassing 3,445 distinct activities. These findings are visually represented in Figure 3 and the process map in Figure 4.



idnumber	Datecreate	eventname	courseid	grouptest	Total	Grade
63xxxxxx88021	28/05/2021 18:32	\core\event\user_loggedin	0	3	83	A
63xxxxxx88021	28/05/2021 18:32	\core\event\dashboard_viewed	0	3	83	A
63xxxxxx88021	28/05/2021 18:32	\core\event\course_viewed	1	3	83	A
63xxxxxx88021	28/05/2021 18:33	\core\event\course_viewed	1	3	83	A
63xxxxxx88021	28/05/2021 18:33	\core\event\dashboard_viewed	0	3	83	A
63xxxxxx88021	28/05/2021 18:34	\core\event\course_viewed	1	3	83	A
63xxxxxx57080	30/05/2021 10:33	\core\event\user_loggedin	0	3	71	B
63xxxxxx57080	30/05/2021 10:33	\core\event\dashboard_viewed	0	3	71	B
63xxxxxx57080	30/05/2021 10:34	\core\event\user_profile_viewed	0	3	71	B
64xxxxxx91018	10/06/2021 10:48	\core\event\user_loggedin	0	2	68	C+
64xxxxxx91018	10/06/2021 10:48	\core\event\dashboard_viewed	0	2	68	C+
64xxxxxx91018	10/06/2021 13:38	\core\event\user_loggedin	0	2	68	C+

Figure 2 Event log data of students learning through the e-learning system.

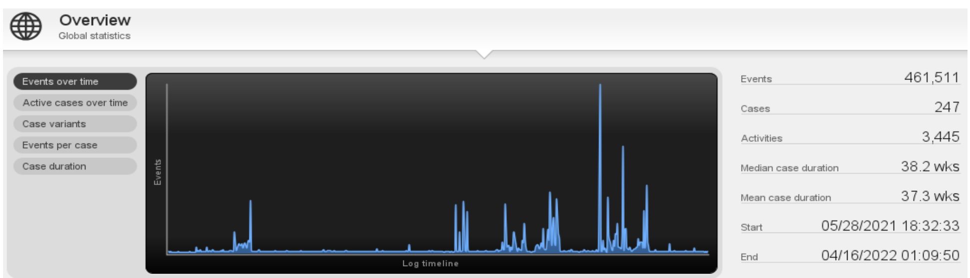


Figure 3 Statistics of the process of learning through the e-learning system.

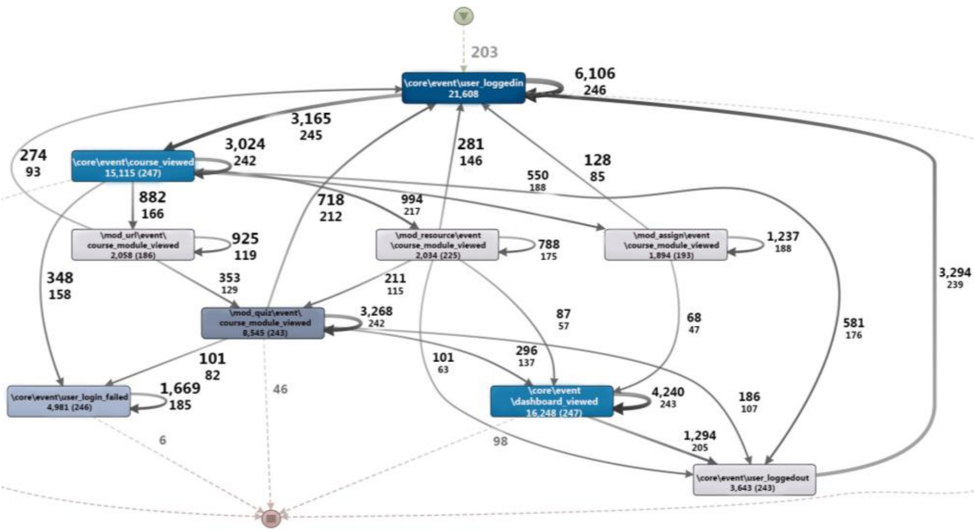


Figure 4 Process Map The process of learning through the e-learning system (Excerpt of "Spaghetti" Process model ca. 16% of the complete model).

From Figure 4, it is observed that the displayed process map exhibits numerous activities and events, along with a large number of inter-event relationships. This results in the Process Map's sprawling spectrogram-like format, challenging the analysis. Therefore, we utilized the Disco tool to filter and divide the data into two parts, as outlined in step 3.2, to analyze the spectrogram behavior of student learning.

3.2 Sample Grouping

From Figure 1, step 6, the samples were divided into two groups to obtain actual event logs for studying the differences in learning behavior. Group 1 consists of students who scored 70% or higher, indicating Good to Excellent performance, ranging from 70.00 to 100.00. Conversely, Group 2 comprises students who scored below 70%, indicating Failure to Almost Good performance, with scores ranging from 00.00 to 69.99. By filtering the event log data using the "Keep Selected" Filtering Mode, it was found that Group 1 comprised 74 individuals, accounting for 29.96%, with 167,502 events occurring. Group 2 comprised 173 individuals, accounting for 70.04%, with 294,009 events occurring. Subsequently, the event log data was exported in CSV format, as shown in Figure 5, for further analysis of the spectrogram behavior of student learning. The analysis included examining the correlation between the frequency of attendance, duration of attendance, and students' academic performance and conducting multiple linear regression analysis factors affecting teaching efficiency. The exported data included:

Case ID column: This column contains unique student identification codes.

Frequency column: This column captures the frequency of system usage based on collected data from user behavior within the system.

DurationMilli column: This column stores the duration of system usage in milliseconds. It includes timestamps for how long each student viewed video media and accessed the system in general.

DurationS column: This column represents the duration of system usage in seconds. It is derived by converting milliseconds to seconds using the formula (milliseconds x 0.001).

Score column: This column contains the overall test score for each student. The maximum score achievable is 100 points.

Group column: This column categorizes students by academic performance. Number 1 denotes the Good to Excellent group, while number 2 denotes the Failure to Almost Good group.

Case ID	Frequency	DurationMilli	DurationS	Score	Group
64xxxxxx49003	455	21785791000	21785835	90	1
64xxxxxx89004	806	19942821000	19942861	86	1
64xxxxxx49004	442	22366135000	22366180	84	1
64xxxxxx89008	930	25749257000	25749308	83	1
63xxxxxx88017	210	20409215000	20409256	83	1
63xxxxxx88018	238	23021211000	23021257	83	1
63xxxxxx88019	167	23020055000	23020101	83	1
63xxxxxx88020	160	20126311000	20126351	83	1
63xxxxxx88021	984	27312706000	27312761	83	1
63xxxxxx88022	185	23026976000	23027022	83	1
63xxxxxx88023	1235	23355740000	23355787	83	1
63xxxxxx88025	116	23020648000	23020694	83	1
63xxxxxx88033	248	23021139000	23021185	83	1

Figure 5 Event log data processed through Process Mining analysis.

3.3 Spectrogram Analysis

We analyzed the spectrogram of students' learning behavior as shown in Figure 1, step 7, using event recording data. Processed with a function in the Matplotlib library of Python, it displays a graph of the relationship between frequency and time (28) of participating in activities through the e-learning system. The frequency of attending class is set as the Y-axis, measured in Hz, while the X-axis represents time, automatically converted from the frequency of the Y-axis using the Matplotlib.Pyplot library, also in Hz (29, 30). Figure 6 illustrates the frequency of participating in activities through the e-learning system for the sample group, which scored a total of 70 and above, comprising 74 individuals. The graph displays high-intensity values of color, demonstrating a linear intensity pattern. In contrast, for the sample group scoring less than 70 percent, consisting of 173 individuals, as depicted in Figure 7, the color intensity appears divided into small boxes distributed on the graph, alternating with lighter colors. This indicates discontinuity in the frequency of participation in learning activities through the e-learning system. The spectrogram chart provides results and analysis of the relationship between frequency (Y-axis) and time (X-axis). Darker colors indicate high-frequency time periods, while brighter colors represent low-frequency periods (7,30,31). We employed a method inspired by Qiang Guo et al., who presented the relationship between harmonic radiation of power lines and magnetic field radiation lines across China using a spectrogram graph. They explained the intensity of colors on the graph as follows: Low-frequency spectrogram lines exhibit bright colors, indicating no radiation. Subsequently, the brightness gradually decreases, with color intensity increasing as frequency increases, suggesting the emission of harmonic radiation from the wires during those periods (7).

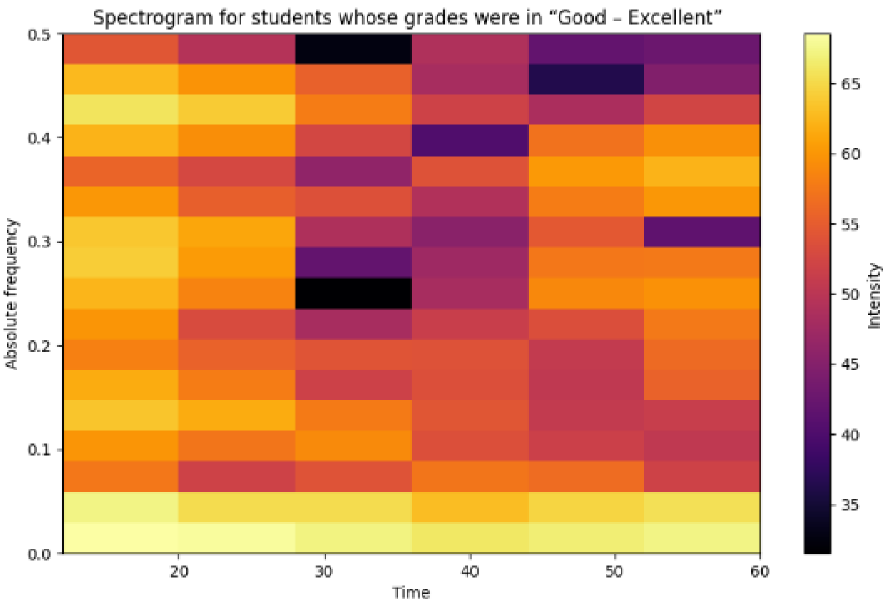


Figure 6 shows the sample group that scored 70% or higher on the overall exam.

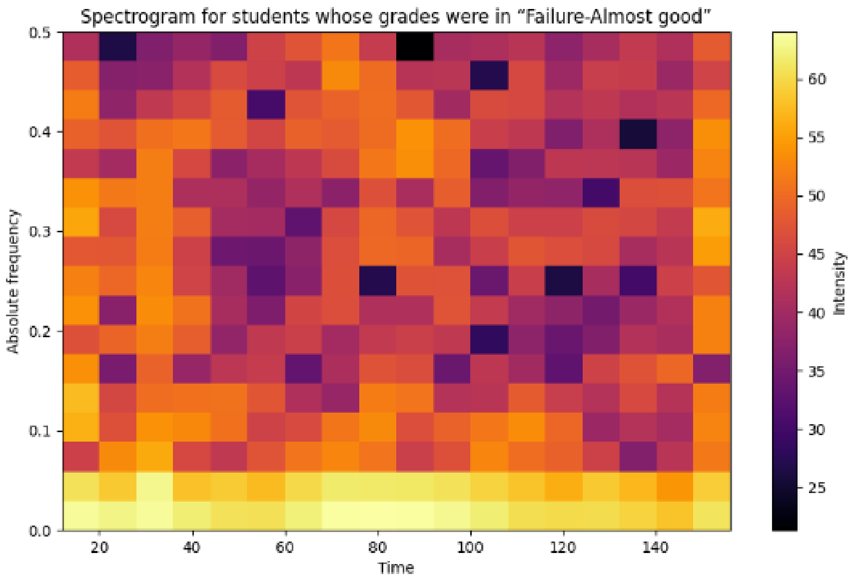


Figure 7 shows the sample group that scored less than 70% on the exam.

3.4 Correlation Analysis

Analyze the Correlation between the frequency of school attendance Length of time to study and academic performance of students studying with the e-learning system, as shown in Figure 1 step 7, using event log data that has been analyzed with Process Mining techniques, as shown in Figure 5. The results of the analysis are shown in Table 1.

Table 1 Presents the results of the correlation analysis between the frequency of school attendance, length of study time, and academic performance of students studying with the e-learning system (n = 247).

		Frequency of attending class	**Duration of time to study**	**Academic results**
Frequency of attending class	Pearson Correlation	-	.263**	.532**
	P	-	.000	.000
	Relationship		Moderate	High to very high
Duration of time to study	Pearson Correlation		-	.133*
	P		-	.037
	Relationship			Negligible

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.

Table 1, results of correlation analysis between school entry events. Study period and the academic performance of students studying with the e-learning system. It was found that the correlation coefficient between the variables that affect the efficiency of teaching through the e-learning system and academic performance is the relationship between the frequency of class attendance. With the study duration, there is a positive relationship with statistical significance at the 0.1 level. There is a moderate relationship. Relationship between frequency of attendance and academic results There is a positive relationship with statistical significance at the 0.1 level. It has the highest level of relationship. and duration of study with academic results. There is a positive relationship with statistical significance at the .05 level, with the lowest level of relationship. Therefore, the frequency of attending classes, the Length of time to study, and the students' learning outcomes are related. It shows that the variables obtained from event recording data are associated with learning through video media in the course. 20 2111 Applied Business Programing used for forecasting is a good variable that can be used to analyze variations in the frequency of activities for comparing the learning behavior of sample groups. We use Best's correlation coefficient to analyze the degree of correlation in this research. The mean values were interpreted according to the criteria of Best (2006) as follows: mean 1.00 - 1.49 = Negligible, 1.50 - 2.49 = Low, 2.50 - 3.49 = Moderate, 3.50 - 4.49 =Substantial, 4.50 - 5.00 = High to very high (32)

3.5 Multiple Linear Regression Analysis

Multiple regression analysis of factors affecting teaching and learning management effectiveness, as shown in Figure 1 step 7, using event log data that has been analyzed with the Process Mining technique, as shown in Figure 5. The results of the analysis are shown in Table 2.

Table 2 Presents the results of a multiple regression analysis of factors affecting the effectiveness of teaching and learning with the e-learning system as the dependent variable, using the Enter method (n = 247)

Model	**Coefficients**		**t**	**p**
	b	**β**		
Frequency of attending class	.013	.537	9.517	<0.001
Duration of time to study	.000	-.007	-.133	.894
$SE_{est} = \pm14.518$; R = .533; R^2 = .284; Adj R^2 = .278; F =48.92; p-value = .000				

** Statistically significant at the .01 level.

From Table 2, the results of the multiple regression analysis found that the factors affecting the efficiency of teaching and learning with the e-learning system were statistically significant at the 0.01 level, with a coefficient of determination (R2) equal to 0.278, indicating that the factors affecting the efficiency of teaching and learning with the e-learning system explain 27.80 percent of the variance. When considering each aspect, it is found that the frequency of class attendance (Beta = 0.537) has a significant effect on the efficiency of teaching and learning with the e-learning system at the 0.01 level.

In summary, the analysis of students' learning behavior using process mining techniques (4,14) from previous articles was utilized to analyze the spectrograms. The analysis examined the relationship between the frequency of school attendance, the length of time spent studying, and academic performance of students studying with the e-learning system, along with conducting multiple regression analysis of factors affecting the efficiency of teaching and learning. It can be clearly confirmed that students who exhibit continuous attendance behavior and demonstrate determination to study and allocate time for studying often achieve better scores on exams compared to students with inconsistent attendance behavior. In Figure 1, Step 8, the insights gained from the data analysis in Step 7 enabled instructors to understand the reasons behind students' poor academic performance and the differences in behaviors between the two sample groups. This knowledge empowered instructors to make informed decisions regarding the development of the teaching and learning process, the improvement of teaching quality, the enhancement of lesson content, and the enrichment of students' learning experiences to foster self-awareness and continuous learning. Consequently, these efforts led to the establishment of best practices in teaching and learning in Steps 9 and 10, tailored to the specific needs of the students.

4. Summary of Research

The analysis results showed that the color intensity values on the spectrogram graphs were high, with a long, continuous dark color. This indicates that the variation in the frequency of learning behavior among students with an overall exam score of 70% and above differs from the sample group that scored less than 70%. This suggests that students who engage in continuous, self-directed learning and consistently participate in activities through the system demonstrate greater determination to learn. These students tend to achieve higher scores than those who attend classes intermittently.

This finding is consistent with research on the behavior analysis of students in video classes (33), which shows that the frequency of class attendance (Beta = 0.537) is a significant factor affecting the efficiency of teaching and learning. The frequency of attending classes has a positive relationship with the duration of school attendance, with statistical significance at the 0.01 level. Therefore, the application of event log data analyzed with process mining techniques, along with spectrogram analysis, correlation analysis, and multiple linear regression analysis, yields consistent results. E-learning systems can be effectively integrated with process mining techniques.

Creating and storing event log data Using the Fluxicon Disco tool, data was filtered to divide the sample according to the desired conditions for in-depth behavioral analysis of learning through the e-learning system. The study was divided into three main components.

1. Creation and integration of event recording data from the e-learning system: The research has collected data from teaching and learning via the e-learning system during the 2019 coronavirus outbreak. The structure of the study has been designed. Create and combine data according to the principles of Process Mining Analysis (24) so that event log data can be analyzed with process mining techniques.

2. Searching for student learning processes using process mining techniques: This involves taking event log data and analyzing the results with the Fluxicon Disco tool using the Fuzzy Miner Algorithm to find processes that show in-depth behavior in accessing the system (14) and define groups for studying differences in learning behavior of students.

3. Data analysis with Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis: Data analysis with these methods will confirm the consistency of the discovered process. To serve as a guideline for decision-making in planning and developing the process for the system to be the driver of teaching and learning through the e-learning system at the educational administrator level. It can be used as a guideline for adjusting educational management policies. Use it as a guideline for setting learning conditions at the teacher level. Motivate, cultivate self-learning, and promote continuous learning.

Research shows that creating and combining event log data from e-learning systems (4) aids in process discovery. How can data analysis using Spectrogram Analysis, Correlation Analysis, and Multiple Linear Regression Analysis be effectively applied? The importance of event log data analyzed using process mining techniques with the Fuzzy Miner Algorithm demonstrates its usefulness in process science (34) and educational process mining (EPM) (11–13). The methods presented in this research do not focus solely on educational management but can also be applied in various sectors such as the business, industrial, tourism, and agricultural sectors. In conclusion, the results of this research involve creating and combining event log data from e-learning systems and investigating student learning processes using process mining techniques. The analysis is tailored to the specified objectives but can be applied to other contexts as well.

The proposed approach offers valuable benefits at the managerial level. By analyzing student behavior on the e-learning platform and utilizing the resulting analytics, lecturers and instructors can gain insights to improve course curricula, determine optimal learning conditions, and motivate self-learning. Self-learning is an essential skill for students in today's era, enabling them to develop themselves, prepare for the future, and promote continuous learning. Ultimately, this approach optimizes the students' learning process. Additionally, it empowers educational institution administrators, managers, and instructors to track and identify distinct student behavioral patterns. This data-driven system enables informed decision-making in the planning process, allowing them to organize teaching and learning effectively through the e-learning platform.

Furthermore, these insights provide valuable guidelines for improving educational management policies. Ultimately, these benefits translate to students through enhanced learning experiences, leading to improved learning outcomes. This facilitates faster adaptation to e-learning, promotes familiarity with self-directed learning, and fosters lifelong learning. Even in new situations or when adapting to other organizations, data preparation following the Process Mining Analysis requirements, as exemplified in Figure 2, ensures continued effectiveness.

Declaration of Conflicting Interests

The authors declared that they have no conflicts of interest in the research, authorship, and this article's publication.

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